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Document Version

Accepted author manuscript

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Citation for published version (APA):

Dimitrov, M., Groves, K., Howard, D., & Lennox, B. (2021). *Model Identification of a Small Fully-Actuated Aquatic Surface Vehicle Using a Long Short-Term Memory Neural Network*. Paper presented at IEEE ICRA 2021, Xi'an, China.

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Model Identification of a Small Fully-Actuated Aquatic Surface Vehicle Using a Long Short-Term Memory Neural Network

Marin Dimitrov¹, Keir Groves¹, David Howard² and Barry Lennox¹

Abstract—A long short-term memory neural network is used to provide a system model that captures the temporal-dynamics of a holonomic, fully-actuated aquatic surface vehicle. As is true in many fields, new developments in robotics often are made in simulation first before being applied to real systems. To simulate an aquatic or aerial robot, a dynamic system model of the robot is required. The more representative the dynamic model is of the real robot, the smaller the simulation-to-reality gap becomes. The performance of the neural network is compared against a classical parametric model, where coefficients of the parametric model were identified using the same data that was used to train the neural network. The results show that the neural network consistently outperforms the classical parametric model and significantly reduces the error between real velocities and estimated velocities. The neural network also demonstrated the ability to capture complex hydrodynamic effects that were not captured in the parametric model. In addition to the performance improvements, the neural network method can be easily adapted to similarly actuated aquatic vehicles by simply retraining, whereas the classical approach would require manual selection of new equation terms. The neural network model that was created has been used in a vehicle simulation and is presently being used as a research tool.

I. INTRODUCTION

A. Motivation

Aquatic surface vehicles can be useful in a range of scenarios such as ship hull inspection, water quality monitoring or nuclear fuel storage pool inspection. Two main factors determine the possible application areas for an aquatic surface vehicle: size and the accuracy with which the vehicle can hold a trajectory or position, here termed control tracking accuracy. For example, a 4.8 m long autonomous surface vehicle (ASV) that used GPS localisation and had control tracking accuracy of 1 m was successfully used to measure a range of water quality properties in a lake [1]. However, this vehicle would not be suitable for use in a smaller confined environment, such as a nuclear fuel storage pool, where a vehicle must be able to control its path and position with much higher accuracy. The need for smaller surface vehicles with high tracking accuracy led researchers at the University of Manchester to develop MallARD (Small Autonomous Robotic Duck) [2]. MallARD is an ASV that was primarily designed to operate in spent nuclear fuel storage pools and achieves a control tracking accuracy of less than 1 cm using a 2D LiDAR as its main sensor. Although designed for use in fuel storage pools, MallARD can be used for

inspection and monitoring purposes in most confined space water applications e.g., process vessels or water storage facilities.

To speed-up development of MallARD, it is useful to have a computer simulation of the robot. Simulation of a complete robot and how it interacts with its surroundings is now commonplace and new innovations are usually tested in simulation before being implemented on the actual system [3].

As well as purely software simulation, a unique robot, termed here a hardware simulation, has been produced that facilitates development of ASVs without the need for a pool [4]. The hardware simulation is a holonomic ground robot that can mimic the physical behaviour of the true target robot, using real sensors and identical software configurations. The hardware simulation is used extensively for development of the MallARD platform.

The hardware simulation is a more realistic alternative that is preferable when testing on the actual robot is expensive or difficult, which is often the case for aquatic robots as they require extended access to pool facilities. Furthermore, connectivity between system components can be validated and electronics tested. An example of a hardware simulation of the El-MallARD robot [4]. El-MallARD is an omnidirectional ground vehicle capable of mimicking the physical behaviour of an aquatic surface vehicle, if a dynamic model is provided.

For both hardware and software simulation, a dynamic system model is required. The accuracy of the model in terms of its ability to predict the physical behaviour of the real robot is important for a number of reasons. First, a highly accurate model allows more testing and development to take place in simulation, which can save time and cost. Second, if the dynamic model is very representative of the real system then the transition between running software in simulation and on the real robot is easier and less prone to error. Finally, the system model can be used as an aid to the robots localisation package, e.g. [5] and [6]. If the model can provide accurate velocity predictions, these can be fused with measurements from other sensors to improve precision of the location estimate [7].

In this work, two different system models of MallARD are compared in terms of their performance, one using a classical parametric approach based on a theoretical model and the other using modern recurrent neural networks. The parametric model and method of identifying parameters has been previously covered in-depth in a previous article by the authors [8]. A key problem that was identified in the

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author's previous work is the choice of appropriate equation terms for inclusion in the model. This is a common problem associated with parametric system models. It can be difficult to correctly include and identify coefficients for complex and often coupled hydrodynamic model parameters. If salient parameters are missed, the model will lose accuracy during certain manoeuvres [9]. Using an appropriate, trained neural network in place of the classical, theoretical model removes the need for manual selection of appropriate theoretical model parameters. This has the potential to provide a more robust and accurate model that is easier to train or identify than a classical parametric model. Therefore, a temporally sensitive long short-term memory (LSTM) neural network was used to provide the dynamic model, as it overcomes the identified weaknesses of the aforementioned parametric approach.

B. Literature review

Within the literature there are various contributions to parametric modelling of both surface and underwater vessels. In their paper [10], Eriksen and Breivik presented a parametric model and a control system for a high-speed aquatic surface robot. The vehicle was 8.45 m long, 2.71 m wide and could reach speeds of up to 18 m/s. A 2 DOF model was implemented because the vehicle was underactuated and operated only in surge and yaw. For parameter identification a weighted linear least squares method was used. Li et al. [11] described the modelling of an unmanned surface vessel with rudderless double thrusters. The vehicle had a catamaran structure and was able to reach up to 1.5 m/s. Due to the low speed, the authors neglected nonlinear drag from the dynamic equation and used linear least squares for parameter identification. Sonnenburg and Woolsey [12] presented a summary of the system identification techniques developed for use on aquatic surface robots covering both parametric and non-parametric approaches.

Although there is a variety of examples of parametric system modelling of aquatic vehicles within the literature, there are significantly fewer contributions related to modelling using neural networks. The example that is most similar to the approach of the authors is presented by Woo et. al. [13], who developed a system model that combined a classical parametric approach with an LSTM neural network to account for nonlinearities. The addition of the neural network to the parametric model led to improvements in model accuracy. The vehicle identified in [13] was significantly different to MallARD, being underactuated and much larger in size. Moreover, in [13] the LSTM network was used to augment a parametric model, meaning two models were required and equation terms still needed to be manually selected. In this paper an LSTM network is used in isolation from the parametric model, removing the need to manually select model parameters.

Neural networks have not been widely used for modelling of aquatic surface vehicles. However, there is a large number of works related to neural networks for dynamic system modelling. For instance, in [14] an artificial neural network

was used to model a 2D damper bearing and the network outperformed a theoretical model that was derived from the fluid mechanics of the damper. Recently, in [15] a combination of neural networks was used for dynamic modelling of a legged robot, specifically representing the actuators with an identified model based on a feedforward neural network. This allowed useful behaviours to be learned in simulation, and sidestep the usual 'reality gap' issues when transferring back to the real robot as motor dynamics were properly represented in the simulation and captured from real-world data.

One of the first papers to model vehicle dynamics with neural networks was applied to identify dynamic models of a helicopter [16], and subsequently used those models to perform aerobatic manoeuvres. The neural network showed significant improvements over other state-of-the-art approaches, especially where dynamics were highly nonlinear and difficult to obtain using standard approaches.

Other examples of nonlinear system identification include the use of convolutional networks [17], or combination with randomized algorithms [18], however, the authors were motivated to use LSTM networks due to their temporal sensitivity and ability to represent time-series dynamics over multiple temporal resolutions.

C. Contribution

The main contributions of this paper are as follows:

- 1) Development of an LSTM recurrent neural network for modelling the dynamic behaviour of a small, fully actuated aquatic surface vehicle;
- 2) A performance comparison between the LSTM neural network model and a classical parametric model with empirically identified coefficients.

II. HARDWARE ARCHITECTURE

A. Hardware components

MallARD, presented in Figure 1, is a holonomic aquatic surface vehicle, designed to operate at low speeds (0-1 m/s) in confined spaces. It consists of two pontoons of length 500 mm, where all the electronic components are encapsulated. When running in manual control, MallARD receives analogue control inputs from a joystick which are translated to thruster outputs. The joystick is connected to a control laptop that wirelessly communicates with an on-board computer. The commands in surge, sway and yaw are transformed into PWM inputs for the individual thrusters using the thrust allocation scheme (Section II-B). PWM signals are sent from a connected microcontroller to the electronic speed controllers which are directly connected to the brushless motors of the thrusters. All systems onboard are powered by an 8 Ah, 22.2 v, 6s Lipo battery. The on-board computer processes data from a 2D LiDAR and runs a SLAM algorithm to estimate the pose of the robot [19]. In addition to manual control, MallARD can follow predefined trajectories and station keep under closed loop trajectory control. A more detailed system design as well as full description of the control systems implemented can be found in [2].

Fig. 1: MallARD in the testing pool that was used for conducting experiments.

B. Thrust allocation

Fig. 2: MallARD's thruster layout in relation to its control inputs.

The thruster layout of MallARD is presented in Figure 2. Throughout this work the always forward (AF) thrust allocation scheme presented in [8] is used. This scheme eliminates the problems associated with deadbands by ensuring that all thrusters are always spinning clockwise and never change direction. When there is no control input, all four thrusters spin clockwise with the same low level of thrust, which due to the symmetric layout of the thrusters generates no net thrust. To move forward, for example, inputs to thrusters 3 and 4 are increased, while no change is made to the level of thrust delivered by thrusters 1 and 2. To rotate clockwise, inputs to thrusters 1 and 4 are increased. Movement that involves inputs in more than one degree of freedom is treated as a linear combination of the thrusters inputs for each of the degrees of freedom. Full detail of the AF thrust allocation scheme is described in [8].

Fig. 3: Schematic diagram showing the choice of earth and body reference frames for MallARD.

III. DYNAMIC MODEL

A. Kinematics and reference frames

Due to its mechanical design, MallARD is stable in roll and pitch. Wave disturbance is small in the pool and for this reason motions in pitch, roll, and heave are neglected in this work. Therefore, the general six degrees of freedom model used for aquatic vehicles [20] can be simplified to three DOF.

Figure 3 presents the coordinate system and reference frames used in this work. The yaw angle is represented by ψ and the robot coordinates in X_e and Y_e by x and y , respectively. The coordinate vector in the earth-fixed frame is $\eta = [x, y, \psi]^T$, and the velocity vector becomes $\dot{\eta} = [\dot{x}, \dot{y}, \dot{\psi}]^T$. The body frame velocities in X_b and Y_b are u and v , while the angular velocity is r . The velocity vector is $\nu = [u, v, r]^T$ and the relationship between the body frame velocity vector and the earth-fixed velocity vector is:

$$\dot{\eta} = R(\psi) \nu \quad (1)$$

where the frame rotation matrix is given by:

$$R(\psi) = \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (2)$$

B. Dynamics

Following Newton's second law of motion and the mainstream conventions (e.g. [11] and [21]) a dynamic model of MallARD in the body frame can be expressed as:

$$\mathbf{M}\dot{\boldsymbol{\nu}} + \mathbf{C}(\boldsymbol{\nu})\boldsymbol{\nu} + \mathbf{D}(\boldsymbol{\nu})\boldsymbol{\nu} = \boldsymbol{\tau}, \quad (3)$$

where,

$$\mathbf{M} = \begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & I_z \end{bmatrix}, \quad (4)$$

$$\mathbf{C}(\boldsymbol{\nu}) = \begin{bmatrix} 0 & 0 & -mv \\ 0 & 0 & mu \\ 0 & 0 & 0 \end{bmatrix}, \quad (5)$$

$$\mathbf{D}(\boldsymbol{\nu}) = \mathbf{D} + \mathbf{D}_N(\boldsymbol{\nu}), \quad (6)$$

$$\mathbf{D} = - \begin{bmatrix} X_u & 0 & 0 \\ 0 & Y_v & 0 \\ 0 & 0 & N_r \end{bmatrix}, \quad (7)$$

$$\mathbf{D}_N(\boldsymbol{\nu}) = \begin{bmatrix} -X_{|u|u}|u| & 0 & 0 \\ 0 & -Y_{|v|v}|v| & 0 \\ 0 & 0 & -N_{|r|r}|r| \end{bmatrix}, \quad (8)$$

$$\boldsymbol{\tau} = \begin{bmatrix} \tau_u \\ \tau_v \\ \tau_r \end{bmatrix} = \begin{bmatrix} X_F F_u \\ Y_F F_v \\ N_F F_r \end{bmatrix} \quad (9)$$

$\mathbf{M}$ is the mass matrix with m_x , m_y and I_z being the total mass in x , total mass in y and moment of inertia around Z_b , respectively. It is assumed that the added mass in x and y is constant. The vector of centripetal forces is represented by $\mathbf{C}(\boldsymbol{\nu})\boldsymbol{\nu}$, the drag forces vector is $\mathbf{D}(\boldsymbol{\nu})\boldsymbol{\nu}$ and $\boldsymbol{\tau}$ is the vector of external forces and torques. The linear drag coefficients are X_u , Y_v , N_r , while the non-linear drag coefficients are $X_{|u|u}$, $Y_{|v|v}$, $N_{|r|r}$. The force inputs to the system are F_u , F_v , F_r with X_F , Y_F , N_F being the associated linear force coefficients. More detailed description of the choice of parameters can be found in [8]. In this paper some of the coupling terms presented in [8] are omitted, because they have negligible effect on the measured accuracy of the model.

IV. EXPERIMENTS AND DATA COLLECTION

Data for the system identification of MallARD was collected in a pool that was 2.4 m wide and 3.6 m long, shown in Figure 1.

In total, 12 datasets were recorded in three repeat experiments using four different motion patterns. Each dataset was between 5 and 6 minutes in length. For the first three datasets S_1 , S_2 and S_3 , MallARD was predominantly excited in X_b (Figure 3) by control inputs in F_u (Figure 2). In the second three datasets S_4 , S_5 , S_6 and third three datasets, S_7 , S_8 , S_9 , excitation was focused on Y_b and ψ by F_v and F_r , respectively. For datasets S_1 to S_9 excitation was induced by pulsing the joypad on a single axis. The period and amplitude of the pulses was varied so that a range of accelerations and velocities were generated. In the final

three datasets S_{10} , S_{11} , S_{12} , MallARD was excited in all degrees of freedom and was driven in squares, circles and figures of eight, which are motions that could be expected in practice. Throughout the experiments, the driver kept the robot at least 0.5 m away from the walls, because if the thrusters do not have open water surrounding them their performance can be affected. Camera footage showing sections of the data collection can be viewed in the video accompaniment to this paper.

The datasets consisted of both recorded joystick control inputs and earth fixed frame coordinates, obtained from the SLAM algorithm output. The joystick generated data at a rate of 100 Hz, while the pose data was created at 15 Hz. The datasets were interpolated so that data points were synchronised at a fixed rate of 15 Hz. Earth-fixed velocities were estimated at each point using the five-point stencil method and body frame velocities were then calculated using Equation 1.

V. MODEL IDENTIFICATION

A. Parametric model identification using least squares fitting

To prepare the parametric model for identification, Equations 3 to 9 in Section III were rearranged as follows with lumped coefficients:

$$\begin{aligned} \dot{u} &= vr + (X_{|u|uc}|u| + X_{uc})u + X_{Fc}F_u \\ \dot{v} &= -ur + (Y_{|v|vc}|v| + Y_{vc})v + Y_{Fc}F_v \\ \dot{r} &= (N_{|r|rc}|r| + N_{rc})r + N_{Fc}F_r \end{aligned} \quad (10)$$

where $X_{|u|uc} = \frac{X_{|u|u}}{m}$, $X_{uc} = \frac{X_u}{m}$, $X_{Fc} = \frac{X_F}{m}$, $Y_{|v|vc} = \frac{Y_{|v|v}}{m}$, $Y_{vc} = \frac{Y_v}{m}$, $Y_{Fc} = \frac{Y_F}{m}$, $N_{|r|rc} = \frac{N_{|r|r}}{I_z}$, $N_{rc} = \frac{N_r}{I_z}$, $N_{Fc} = \frac{N_F}{I_z}$. It was assumed that the added mass in X_b and Y_b are of equal magnitude, because the robot moves with low velocity and acceleration. Equation 10 was discretised so that coefficients could be determined using the least squares method. Datasets S_1 , S_2 , S_4 , S_5 , S_7 , S_8 , S_{10} and S_{11} were used in the identification procedure, while datasets S_3 (excitation in X_b), S_6 (excitation in Y_b), S_9 (excitation in ψ) and S_{12} (combined motion) were set aside for testing. Detail of the procedure used to identify coefficients can be found in [8] but is omitted here for brevity.

B. LSTM network

An LSTM recurrent neural network was also used to identify the dynamic system model. Since the dynamic behaviour of MallARD is temporally sensitive and depends not only on present inputs, but also on previous inputs and outputs, the LSTM architecture was chosen as it is able to capture temporal dynamics.

Our network architecture is shown in Figure 4, with the structure of an individual cell is presented in Figure 5. The three input vectors to the cell are c_{t-1} , h_{t-1} and x_t , where x_t is a 1x6 vector with three of the columns containing the force inputs F_x , F_y and F_z and the other three being the body frame velocities u_t , v_t and r_t . The output from each cell is h_t and c_t is the memory control variable that is passed to the next cell. Each sigmoid and hyperbolic tangent layer

Fig. 4: Schematic of the full LSTM recurrent neural network used to model robot's dynamic behaviour.

Fig. 5: A single cell of the LSTM network, where x_t is the input at the current time step, h_t is the output at the current time step and c_t are values passed between the LSTM cells acting as memory control.

Figure 5) was comprised of 50 neurons. The network was trained to predict the output data using fifteen timesteps, therefore fifteen stacked LSTM cells were used, predicting velocities in (X_b), (Y_b) and (ψ) at timestep t , using previous velocities and force inputs from timestep $t-15$ to $t-1$. The network was tested with the number of cells ranging from 2 to 30 and error minimisation converged at 15 cells.

A layer of three linear output neurons provided the model output (body frame velocities in 3 degrees-of-freedom). Datasets used for training the network were the same as those used for identification of the parametric model. A variety of cost functions and batch sizes were explored. Best results were achieved using a mean squared error cost function and a batch size of 1024. The network was trained with 20 epochs using the ADAM training optimizer [22], which provided heightened performance compared to other optimisers (e.g., RMSprop [23]) during initial testing.

VI. RESULTS AND DISCUSSION

A. Single axis excitation

The main purpose of the dynamic model is to allow both software and hardware simulation of MallARD's dynamic behaviour. Therefore, the two dynamic models were tested based upon their ability to predict velocities over a long time horizon, using only initial conditions, i.e. an infinite step-ahead model. The efficacy of the LSTM network is

Fig. 6: Plots (a) and (b) show the measured velocity u in X_b taken from dataset S_3 against the estimated velocity in X_b for the classical parametric model and the LSTM model respectively; Plot (c) displays the control input F_u .

compared against the classical parametric dynamic model, and accompanying coefficient identification procedure, that was previously developed by the authors. The datasets used for testing the dynamic models were previously unseen datasets S_3 , S_6 , S_9 and S_{12} . These datasets were not used in any of the training or identification procedures.

Considering dataset S_3 , where the inputs from the joystick were predominantly in F_u , Figure 6 shows that both the classical parametric model and the LSTM network perform well and with similar error. Table I presents the RMS error between the estimated and the actual velocities u , v and r for the respective S_3 , S_6 and S_9 datasets. These results show that the LSTM network performs slightly better overall when excitation is predominantly in a single degree-of-freedom and velocity predictions are made on the same axis. However, it was noticed during experiments that when the robot was excited in F_u (on X_b), MallARD began to rotate, indicating coupling between linear motion in X_b and rotation about Z_b . Attempts to model this coupling by adding various parameters to the parametric model was unsuccessful but the LSTM model was able to model this coupling effect without modification. This can be observed in Figure 7, where estimated and actual yaw velocities are plotted for both dynamic models for dataset S_3 . In dataset S_3 , excitation was predominantly in F_u ; excitation in F_r was only used to correct the robot's orientation. In the time region between 90 s and 140 s (Figure 7), there was no excitation in F_r but there was induced velocity in r due to excitation in F_u and the LSTM network clearly outperforms the parametric model in this region.

B. Multi-axis excitation

The improvements in model accuracy of the LSTM network when compared to the classical model is more prominent when tested on the combined motion dataset (S_{12}). Figure 8 shows the LSTM model estimates tracking the real v

TABLE I: RMS errors between predicted velocities and measured velocities.

Body Frame Velocity	Dataset	LSTM	Classical Model
u	S_3	0.026 m/s	0.032 m/s
v	S_6	0.027 m/s	0.026 m/s
r	S_9	0.038 rad/s	0.062 rad/s

Fig. 7: Plots (a) and (b) show the measured angular velocity r about Z_b taken from dataset S_3 against the estimated velocity for the classical parametric model and the LSTM model respectively; Plot (c) displays the control input F_r .

velocities much closer than the parametric model. Similar results were derived for u and r using the S_{12} dataset. This is evident in the histograms that are presented in Figure 9. The histograms presenting error from the LSTM network show consistently lower mean error and lower deviation of errors than the histograms associated with the classical parametric model.

VII. CONCLUSIONS

An LSTM recurrent neural network has proven to be a useful method for generating a system model that can reproduce the temporal-dynamics of an aquatic vehicle. The LSTM model developed in this paper was demonstrated to be capable of producing accurate and reliable velocity estimates over long time periods (250 s) when provided with the vehicle's control inputs. When compared directly against a classically derived parametric model, the LSTM model showed clear improvements in accuracy, particularly in the more realistic case of control inputs in multiple degrees of freedom. The LSTM network reduced the RMS velocity estimation error by an average (mean) of 35.67 % compared to the classical parametric model, in the more realistic case of control inputs across all three degrees-of-freedom.

The neural network also requires less manual setup; this makes it both faster to deploy and less prone to errors caused by the selection of equation terms.

Fig. 8: Plots (a) and (b) show the measured velocity v in Y_b taken from dataset S_{12} against the estimated velocity in Y_b for the classical parametric model and the LSTM model respectively; Plot (c) displays the control input F_v .

Fig. 9: Histograms presenting the prediction error of the two different models for velocities u in X_b , v in Y_b and r about Z_b for the S_{12} dataset.

The trained LSTM neural network is presently being used to facilitate research on the Mallard ASV in both software and hardware simulations (see Section I-A).

ACKNOWLEDGMENT

This research was funded by the Engineering and Physical Sciences Research Council under grant: EP/P01366X/1

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